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Design of Intelligent Political Test Paper Generation Method Based on Improved Intelligent Optimization Algorithm

Qing Wan[1,*]

[1] School of Marxism Xinxiang College, Xinxiang 453003, Henan, China

Abstract

With the development of artificial intelligence, computer intelligent grouping, as a research hotspot of political ideology examination paper proposition, can greatly shorten the time of generating examination papers, reduce the human cost, reduce the human factor, and improve the quality of political ideology teaching evaluation. Aiming at the problem that the current political ideology examination paper-grouping strategy method easily falls into the local optimum, a kind of intelligent paper-grouping method for political ideology examination based on the improved stock market trading optimisation algorithm is proposed. Firstly, by analyzing the traditional steps of political test paper generation, according to the index genus of the grouping problem and the condition constraints, we construct the grouping model of political thought test questions; then, combining the segmented real number coding method and the fitness function, we use the securities market trading optimization algorithm based on the Circle chaotic mapping initialization strategy and adaptive t-distribution variability strategy to solve the grouping problem of the political thought test. The experimental results show that the method can effectively find the optimal strategy of political thought exam grouping, and the test questions have higher knowledge point coverage, moderate difficulty, and more stable performance.

Keywords:intelligent political test paper generation methods, stock market trading optimisation algorithms, Circle chaos mapping, adaptive t-distribution variation strategies

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*Corresponding author. Email: 15936570912@139.com

1. Introduction

University evaluation of the teaching effect of political thought is one of the important indicators of the overall teaching work of university teachers of political thought, and the teaching evaluation method of political thought is generally carried out from the teaching content, teaching method, teaching attitude, teaching effect, teaching ability and other aspects of the evaluation [1]. University political thought paper examination results as one of the most important ways to evaluate the teaching of political thought, not only to test the teaching quality of political thought, but also to examine the ability of political thought teachers to make questions [2]. University political thought paper examination firstly needs teachers to group the political thought paper [3]. The traditional political thought examination paper is completed manually, which not only consumes a lot of teaching resources, but also has a strong personal subjective factor [4]. With the development of artificial intelligence, computer intelligent grouping as a research hotspot of political thought test paper proposition can greatly shorten the time of generating test papers, reduce the cost of manpower, reduce the human factor, and improve the quality of evaluation of political thought teaching [5]. Intelligent grouping technology is to select suitable test questions from the test bank through artificial intelligence technology to form a test paper that meets the requirements [6]. Intelligent grouping of political thought test papers is one of the application fields of intelligent grouping, and its efficiency and quality depend entirely on the design of the question drawing algorithm [7]. The problem of intelligent grouping of political thought test papers is to use the grouping optimisation algorithm to quickly and accurately extract a set of questions that meet the requirements from the political thought test bank, which is a multi-objective and multi-constraint global optimisation problem [8]. Commonly used grouping methods include automatic grouping methods based on random extraction [9], automatic grouping methods based on depth and breadth search algorithms [10], intelligent grouping methods based on intelligent optimisation algorithms [11], and intelligent grouping methods based on data mining and knowledge discovery [12]. Automatic grouping methods based on random extraction are simple to implement, but the repetition rate is high; automatic grouping methods based on depth and breadth search algorithms are easy to implement, but the time overhead is large; grouping methods based on data mining and knowledge discovery take a long time; automatic grouping methods based on intelligent optimisation algorithms have a stronger search capability and faster convergence speed. Current automatic grouping methods based on intelligent optimization algorithms include genetic algorithms [13], particle swarm optimization algorithms [14], Harris Hawk optimization algorithm [15], internal search optimization algorithm [16], grey wolf optimization algorithm [17], marine predator algorithm [18] and other methods. Although intelligent grouping strategies based on intelligent optimisation algorithms have strong search capability, they are prone to premature convergence and fall into local optimum [19].

Aiming at the current grouping strategy effect quality is not high, the question diversity is poor, the search optimisation is easy to fall into the local optimal and other problems, this paper puts forward a hybrid strategy based on the improvement of human heuristic optimization algorithm intelligent grouping method of political thought exam. Firstly, we analyse the steps of automatic grouping strategy and construct the grouping model of political thought exam questions; then we use the improved stock market trading optimization algorithm [20] to solve the grouping problem of political thought exam questions. The algorithm test results show the feasibility, high efficiency and good real-time performance of the proposed method.

2. Analysis of the problems with the Smart Political Thought group of papers

2.1. Analysing the process of assembling volumes

In order to generate there is a compliant paper, the grouping steps are analysed in accordance with the traditional grouping thinking process, which is shown in **Figure 1**.

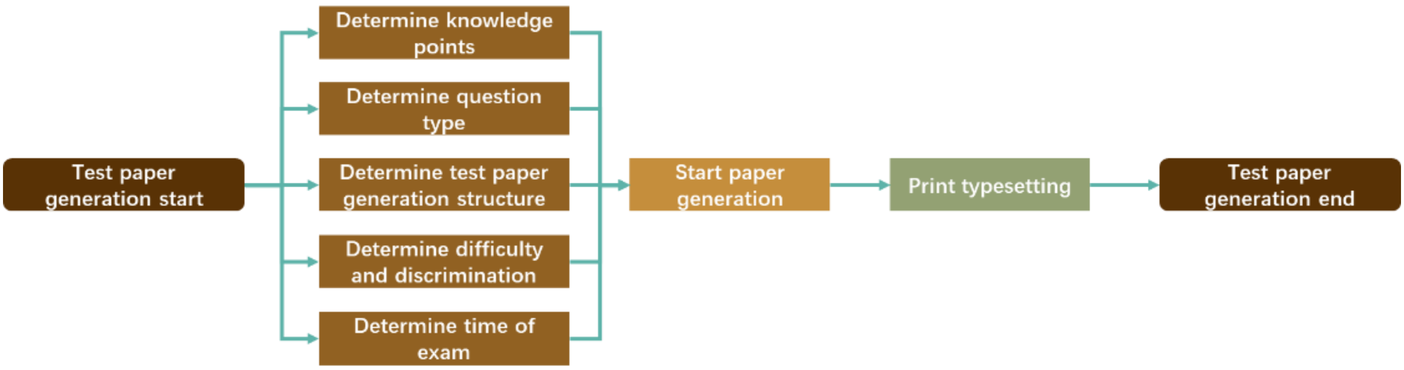


Figure 1 Traditional grouping

As can be seen from Figure 1, grouping volumes generally includes the following steps [21]:

a) Determine the scope of knowledge. Within the scope of the designated examination, analyse the key elements, the elements that require focus and the elements that require a brief understanding;

(b) Determining the types of questions. Examination papers generally include judgement questions, multiple-choice questions, short-answer questions, Chinese character entry questions, etc., and determine the number of questions in each category;

(c) Determine the structure of the examination paper. Determine the proportion of each chapter in the overall paper, i.e., the distribution of points in the paper;

(d) Determining the level of difficulty and differentiation of the examination paper. The main consideration in determining the level of difficulty and differentiation is the reliability and validity of the examination paper;

e) Determination of examination time. Estimate the examination time based on the type of questions, number of questions and structure of the examination paper;

f) Beginning of the formation of volumes and typesetting for printing.

2.2. Intelligent Political test paper generation Mathematical Modelling

According to the analysis of the grouping steps, summarise the grouping constraints, design the grouping index function, and construct the intelligent political test paper generation mathematical model in **Figure 2**.

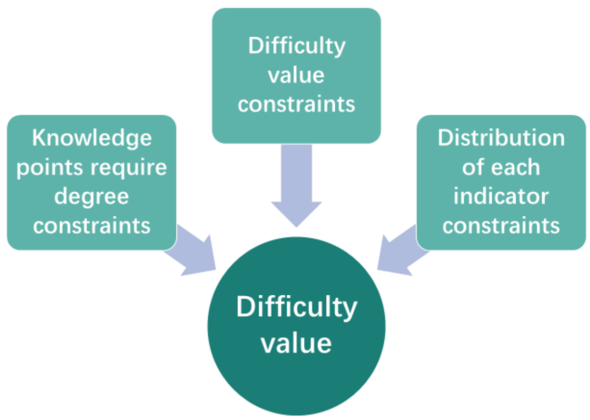


Figure 2 Mathematical model of automated paper grouping

(1) Grouping indicators

The intelligent political test paper generation model proposed in this paper uses the difficulty value of the test question as the grouping indicator function. Difficulty value of a test question is the rate of all subjects losing marks on the question [22], which is calculated by the following formula:

$$M = 1 - \frac{\bar{X}}{S} \tag{1}$$

Where M indicates the difficulty value of the question, $\bar{X}$ indicates the average of the historical scores for the question, and S indicates the full score value for the question.

(2) Group volume constraints

Each question in the question bank of this political thought exam contains m-dimensional vectors of question number, question type, difficulty, the index system to which it belongs, score, and proportion of the degree of knowledge required, i.e. $(a_1, a_2, \cdots, a_m)$. Assuming that the question bank has n questions, it forms the question bank matrix A :

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \tag{2}$$

1) Knowledge point requirement degree constraints

The degree of knowledge requirement is divided into key mastery, secondary mastery, and general knowledge [23]. According to the quality assessment proposition experience, the closer the distribution ratio of the assessment points of a test paper is to 5:3:2, the more scientific the proposition ratio of the test paper is, and the more likely that the test paper results will be normally distributed, so the constraints are as follows:

$$\sqrt{\left(\frac{h}{n} - \frac{1}{2}\right)^2 + \left(\frac{i}{n} - \frac{3}{10}\right)^2 + \left(\frac{j}{n} - \frac{1}{5}\right)^2} = 0 \tag{3}$$

Among them, n indicates the total score, and h , i and j indicate the allocated scores for the assessment points of focus, secondary focus and general respectively.

2) Difficulty value constraints [24]

The expected difficulty level of the question is categorised as "hard", "harder", "easier", "easier", and "easier". The difficulty constraints of the test questions are:

$$\sqrt{\left(p^1 - p\right)^2 + \left(q^1 - q\right)^2 + \left(r^1 - r\right)^2 + \left(s^1 - s\right)^2} = 0 \tag{4}$$

Among them, p^1 , q^1 , r^1 and s^1 denote the expected scores for the difficulty levels of "difficult", "harder", "easier" and "easier" respectively, while , , and denote the expected scores for the difficulty levels of "difficult", "harder", "easier" and "easier" respectively. p , q , r and s denote the actual scores for the difficulty levels of "difficult", "harder", "easier" and "easier" respectively. , , and denote the actual scores for the difficulty levels of "difficult", "harder", "easier" and "easier" respectively.

3) Distributional constraints across indicators [25]

The indicators are divided into 10 elements, and the weights of the indicators are translated into percentages, as shown in **Figure 3**. The distribution constraints for each indicator are:

$$\left|\frac{a}{m}-11.4\%\right|+\left|\frac{b}{m}-11.4\%\right|+\left|\frac{c}{m}-11.4\%\right|+\left|\frac{d}{m}-11.4\%\right|+\left|\frac{e}{m}-11.4\%\right|+ \\ \left|\frac{f}{m}-8.6\%\right|+\left|\frac{g}{m}-8.6\%\right|+\left|\frac{h}{m}-5.6\%\right|+\left|\frac{i}{m}-10.3\%\right|+\left|\frac{j}{m}-10.3\%\right|=0 \tag{5}$$

Where m is the total score, a , b , c , d , e , f , g , h , i , and j represent the scores of the C13, C14, C15, C16, C17, C18, C19, C20, C21, and C22 indicator categories of the test questions, respectively.

Index	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22
Total weight	0.026	0.026	0.026	0.026	0.026	0.020	0.020	0.013	0.024	0.024
Relative weight %	11.4	11.4	11.4	11.4	11.4	8.6	8.6	5.6	10.3	10.3

Figure 3 Transformation of indicator weights

3. Optimisation algorithms for securities market trading and their improvement strategies

3.1. Optimisation algorithms for trading in securities markets

Stock exchange trading optimization (SETO) [26] is an algorithm inspired by the trading and changing behaviour of stocks. Stock exchange trading optimization algorithm is a swarm intelligent optimization algorithm where each stock represents a candidate solution to the problem and the search optimisation is done by finding the most profitable stock. The algorithm iterates the optimisation operators including rise, fall and exchange operation operators. Finally, the most profitable share is reported as the optimal solution.

(1) Optimisation mechanisms

1) Population initialisation

To solve the optimisation problem, the first step of the SETO algorithm is to generate an initial population. Each solution in the population is considered as a stock. The population is defined as follows:

$$S=\left[S_1,S_2,\cdots,S_N\right]^T \tag{6}$$

where N is the population size and individuals in the population S_i are specified as:

$$S_i=\left\{s_{i1},s_{i2},\cdots,s_{iD}\right\} \tag{7}$$

Where s_{ij} denotes the jth dimension taken by the ith individual, which is initialised as follows:

$$s_{ij}=l_{ij}+\phi_{ij}\cdot\left(u_{ij}-l_{ij}\right) \tag{8}$$

where ϕ_{ij} denotes a random number between 0 and 1, and u_{ij} and l_{ij} denote the upper and lower dimensions of the search space, respectively.

Individual stocks are evaluated by modelling the stock's earnings value, which is calculated as follows:

$$f_i=f\left(S_i\right)=f\left\{s_{i1},s_{i2},\cdots,s_{iD}\right\} \tag{9}$$

Where, f_i denotes the fitness value of the ith stock individual S_i .

In the stock trading process, each stock has a certain number of buyers and sellers, i.e., sellers and buyers. To define the initial traders, a random initialisation mechanism is used. To achieve this mechanism, the normalised fitness value nf_i is calculated as follows:

$$nf_i=\frac{f_i-\min\left(M\right)}{\sum_{k=1}^{N}\left(f_k-\min\left(M\right)\right)},M=\left\{f_k\,\middle|\,k=1,2,\cdots,N\right\} \tag{10}$$

S_i The number of traders is calculated as follows:

$$T_i=\left[nf_i\times T\right] \tag{11}$$

Where, T is the total number of traders and T_i is the trading volume of stock S_i . During the optimisation of the SETO algorithm, the total trading volume remains unchanged. The number of buyers and sellers of stock S_i is calculated as follows:

$$b_i = \left[r \times T_i \right] \tag{12}$$

$$s_i = T_i - b_i \tag{13}$$

where b_i and s_i denote the number of buyers and sellers, and r is a random number between $[0,1]$ that follows a uniform distribution.

2) Rising operation operator

Upward operation mainly simulates the growth of stock price. At this stage, the stock can move to a higher price and the highest price stock can reach the optimal point. The formula for simulating the upward operation operator is as follows:

$$S_i(t+1) = S_i(t) + R \times \left(S^g(t) - S_i(t) \right) \tag{14}$$

where $S_i(t)$ denotes the i-th stock individual for the t-th iteration, R denotes a D-dimensional random vector, and $S^g(t)$ denotes the optimal solution for the t-th iteration. The parameter R increases the amount of random deviation to help individuals escape from the local optimum and explore more spatial regions, and $r_j \in R$ is defined as follows:

$$r_j = U\left(0, pc_i \times d_1\right) \tag{15}$$

Where U generates uniformly distributed random numbers in the range of $\left[0, pc_i \times d_1\right]$. pc_i is the bid-ask ratio of the stock S_i , and d_1 denotes the normalised distance between $S_i(t)$ and $S^g(t)$:

$$d_1 = \frac{\sqrt{\sum_{j=1}^{D} \left(S_j^g(t) - S_{ij}(t) \right)^2}}{ub - lb} \tag{16}$$

where ub and lb denote the upper and lower bounds of the search space, respectively. Generally, the higher the demand for a stock, the higher the stock value growth. The parameter pc_i simulates the impact of stock growth demand, which is defined by the number of buyers, and is calculated as follows:

$$pc_i = \frac{b_i}{s_i + 1} \tag{17}$$

In order to avoid pc_i crossing the boundary, the parameter pc_i is limited to the range $[0, 2]$, which is calculated as follows:

$$pc_i = \min\left(\frac{b_i}{s_i + 1}, 2 \right) \tag{18}$$

During the upward phase, the demand for stocks grows, simulating an increase in the number of buyers and a decrease in the number of sellers:

$$b_i = b_i + 1 \tag{19}$$

$$s_i = s_i - 1 \tag{20}$$

In the ascent phase, the SETO algorithm moves away from the current search space to explore different search areas.

3) Falling operation operator

The decline operation operator mainly simulates the decline in stock price, and the specific simulation formula is as follows:

$$S_i(t+1) = S_i(t) - W \times \left(S_i^l(t) - S_i(t) \right) \tag{21}$$

where $S_i^l(t)$ denotes the current local optimal solution of the ith stock, W denotes a D-dimensional random vector, and $w_j \in W$ is defined as follows:

$$w_j = U\left(0, nc_i \times d_2\right) \tag{22}$$

Where U generates uniformly distributed random numbers in the range of $\left[0, nc_i \times d_2\right]$. nc_i is the sell-buy ratio of the stock S_i , and d_2 denotes the normalised distance between $S_i(t)$ and $S_i^l(t)$:

$$d_2 = \frac{\sqrt{\sum_{j=1}^{D} \left(S_{ij}^l(t) - S_{ij}(t) \right)^2}}{ub - lb} \tag{23}$$

$$nc_i = \min\left(\frac{s_i}{b_i + 1}, 2 \right) \tag{24}$$

During the decline phase, the supply of stocks increases. In each iteration number, sellers increase and buyers decrease in the decline phase:

$$s_i = s_i + 1 \tag{25}$$

$$b_i = b_i - 1 \tag{26}$$

During the downward phase, the SETO algorithm controls that the buyers and sellers of the stock will not exceed the total number of traders.

4) Exchange operation operator

In the trading phase, the trader uses the most profitable stock to replace the cheapest stock. In this phase, the trader sells the worst stock and buys the best stock.The SETO algorithm simulates stock trading by selecting a seller from the worst stock queue to be assigned to the best stock queue. This mechanism of operation allows stocks to be attracted by traders. First, the worst stock is acquired as follows:

$$\begin{aligned} &S_{worst} = S_w \; where \quad f\left(S_w\right) < f\left(S_j\right) \\ &\forall j = 1, 2, \cdots, N, w \neq j \end{aligned} \tag{27}$$

Then, the worst stock queue removes one of the sellers and adds it to the best stock queue and the optimal stock S_{best} definition is obtained as follows:

$$\begin{aligned} &S_{best} = S_b \; where \quad f\left(S_b\right) < f\left(S_j\right) \\ &\forall j = 1, 2, \cdots, N, b \neq j \end{aligned} \tag{28}$$

The exchange operation operator increases the population size. In the process, the operation decreases the number of sellers and increases the number of buyers. As a result, the buyer-seller ratio increases and the likelihood of the stock rising increases.

5) RSI Calculation

The SETO algorithm uses the RSI indicator to identify stocks rising or falling. As the RSI value increases, SETO performs up or down model as follows:

$$\begin{cases} \text{rising} & RSI \leq 30 \\ \text{falling} & RSI \geq 70 \\ p \times \text{rising} + (1-p) \times \text{falling} & 30 < RSI < 70 \end{cases} \tag{29}$$

where p is a binary random number and $p \in \{0,1\}$, is computed as follows:

$$p = \begin{cases} 1 & rand \geq 0.5 \\ 0 & else \end{cases} \tag{30}$$

where $rand$ denotes a random number between 0 and 1. For the ith stock, the RSI is calculated as follows:

$$RSI = 100 - \frac{100}{1+RS} \tag{31}$$

The simple moving average method was used to calculate relative intensities:

$$RS = \frac{\sum_{i=1}^{K} P_i}{\sum_{i=1}^{K} N_i} \tag{32}$$

Where P_i and N_i denote upward and downward price changes respectively. K denotes the RSI trading time frame, which is set to 14 in the SETO algorithm. The formulas for P_i and N_i are as follows:

$$P_i = \begin{cases} 1 & if\left(f_i(t) - f_i(t-1)\right) > 0 \\ 0 & otherwise \end{cases} \tag{33}$$

$$N_i = \begin{cases} 1 & if\left(f_i(t-1) - f_i(t)\right) > 0 \\ 0 & otherwise \end{cases} \tag{34}$$

where $f_i(t)$ and $f_i(t-1)$ denote the fitness values for the current versus previous iteration counts, respectively.

6) Iteration termination

The iterative termination conditions of the SETO algorithm include the following: a) the optimisation iteration reaches the maximum number of iterations; b) the number of evaluations reaches the maximum number of evaluations; and c) the optimal solution no longer changes.

(2) Algorithmic steps

According to the location update strategy of SETO algorithm, the pseudo-code of algorithm operation is shown in **Figure 4**, and the algorithm step-by-step process is as follows:

Step 1: Set the number of stocks N and the maximum number of iterations of the algorithm $t_{\max}$ to initialise the location information using the uniform random distribution strategy;

Step 2: Calculate the fitness of each stock $f(S)$, find the position of the current optimal stock $S^g(t)$ and keep it;

Step 3: Determine the number of shares to be traded;

Step 4: Calculate the RSI and determine whether to execute an up or down model;

Capture 5: When $RSI \leq 30$, execute the rising operation operator to update the stock position information; when $RSI \geq 70$, execute the falling operation operator to update the stock position information; when $30 < RSI < 70$, determine the size between the random number r and 0.5 to determine the rising or falling model to update the position information;

Step 6: At the end of the position update, the fitness of each stock is calculated and compared with the position of the previously retained optimal stock, and if it is better, it is replaced using the new optimal solution;

Step 7: Determine whether the current calculation reaches the maximum number of iterations, if so, the optimal solution is obtained and the calculation is finished, otherwise go to the next iteration and return to step 3.

```
Algorithm: SETO
Initialize AOA parameters;
Initialize population of shares;
Evaluate initial population and update best share with best value;
While t<=tmax do
    for each share do
        if RSI<=30
            Carry out rising operator;
        elseif RSI>=70
            Carry out falling operator;
        else
            Carry out rising and falling phase;
        end
        Carry out exchange phase;
        Calculate RSI;
    end
    Evaluate object and update best object;
    t = t+1;
end
Output best solution.
```

Figure 4 Pseudo-code of SETO algorithm

3.2. Improved SETO algorithm

(1) Improvement Strategies

By analysing the optimization strategy of SETO algorithm, the initialization strategy distribution situation is random, and it is easy to appear uneven distribution and pile-up; SETO algorithm adopts the ascending operation operator still searching and exploring around the optimal solution, and it will fall into the local optimal problem in the late iteration. In view of the above problems, this paper adopts two strategies to improve the SETO algorithm, the specific operation is as follows:

1) Circle chaotic mapping initialisation strategy

Compared with the random initialisation of the population, the use of Circle chaotic mapping to initialise the population [27] results in a more uniform distribution of the population and the algorithm has a stronger global search capability.The specific model of the Circle chaotic mapping initialisation strategy is as follows:

$$x_{i+1} = \mathrm{mod}\left(x_i + 0.2 - \frac{0.5}{2\pi}\sin\left(2\pi \cdot x_i\right), 1\right) \quad (35)$$

Where, mod denotes the residual function and x_{i+1} denotes the i+1th mapping value.

2) Adaptive t-distribution variation strategy

The shape of t-distribution curve is related to the size of the degree of freedom n. The smaller the value of n is, the flatter its curve is, the lower the middle of the curve is, and the higher the tail of the curve is warped bilaterally, $t(n\to\infty)\to N(0,1)$, $t(n=1)\to C(0,1)$, of which $N(0,1)$ is a Gaussian distribution, and $C(0,1)$ is a Cauchy distribution, i.e., standard Gaussian and Cauchy distributions are the two bounded special-case distributions of the t-distribution [28]. In order to overcome the problem of the rising operation operator falling into local optimality, this paper adopts the adaptive t-distribution variation strategy, the specific formula is as follows:

$$S_i(t+1) = S_i(t) + R\times\left(S^g(t) - S_i(t)\right) + S_i(t)\cdot t(iter) \quad (36)$$

Where, $t(iter)$ denotes the t-distribution with the number of iterations $iter$ as the parameter degrees of freedom. This strategy adds the t-distribution random interference term $S_i(t)\cdot t(iter)$ on the basis of the rising strategy of SETO algorithm to make full use of the information interference of the current population, so that the individuals can jump out of the local optimum and converge to the global extreme point, and at the same time, the convergence speed is improved. In the early stage of the search, the t-distribution variant approximates the Cauchy distribution variant, and the algorithm has good global search ability; in the late stage of the algorithm, the t-distribution variant approximates the Gaussian distribution variant, and the algorithm has good local exploitation ability; in the middle stage of the algorithm, the t-distribution variant is between the Cauchy distribution variant and the Gaussian distribution variant. The strategy combines the advantages of Gaussian and Cauchy operators, which improves the global explorability and local exploitation of the algorithm.

(2) Steps to improve the algorithm

According to the optimisation mechanism and improvement strategy of SETO algorithm, this paper proposes a SETO algorithm based on Hybrid Strategy (HSSETO), the specific flowchart is shown in **Figure 5**, and the algorithmic step-by-step process is as follows:

Step 1: Set the number of stocks N and the maximum number of iterations of the algorithm $t_{\max}$, and initialise the location information using the Circle chaotic mapping initialisation strategy;

Step 2: Calculate the fitness of each stock $f(S)$, find the current optimal position $S^g(t)$ and keep it;

Step 3: Determine the number of shares to be traded;

Step 4: Calculate the RSI and determine whether to execute an up or down model;

Capture 5: When $RSI \le 30$, execute the rising operation operator based on adaptive t-distribution variation strategy to update the stock position information; when $RSI \ge 70$, execute the falling operation operator to update the stock position information; when $30 < RSI < 70$, determine the size between the random number r and 0.5 to determine the rising or falling model to update the position information;

Step 6: Calculate the fitness of each stock and update the optimal solution;

Step 7: Determine whether the current computation has reached the maximum number of iterations.

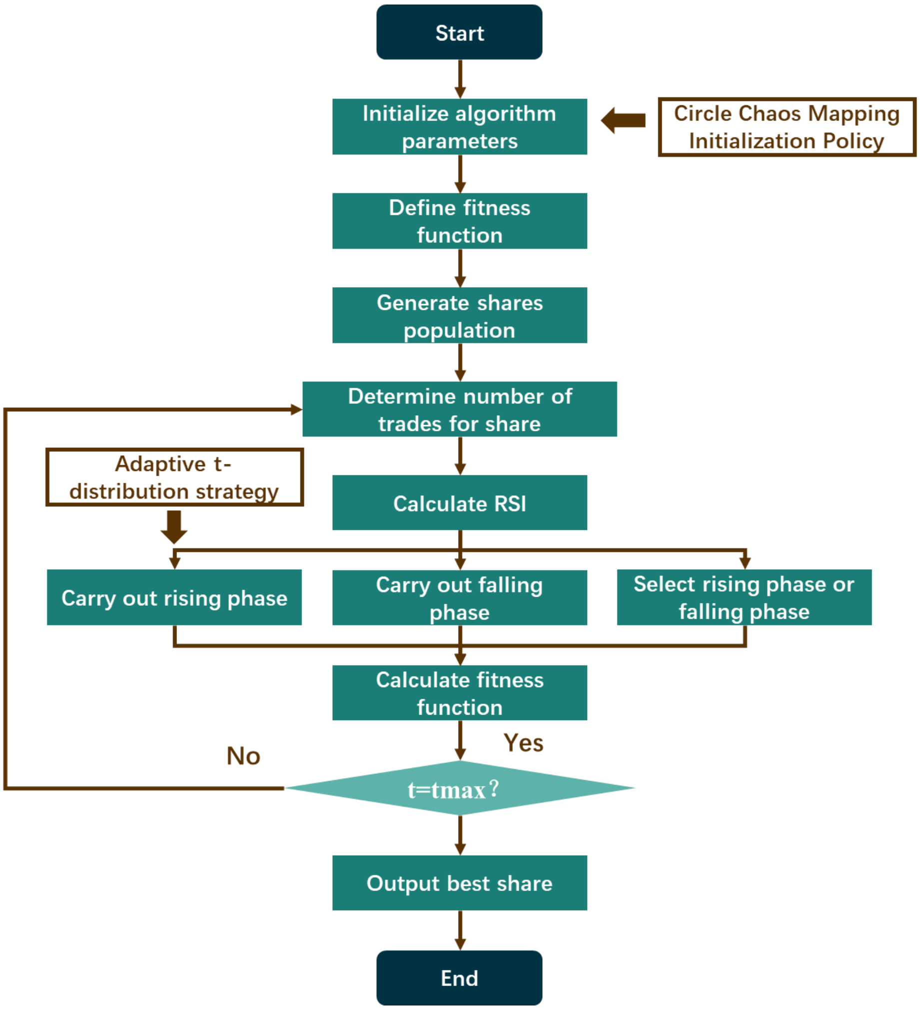


Figure 5 HSSETO algorithm flow

4. The design idea of intelligent political test paper generation method based on HSSETO algorithm

4.1. Coding scheme design

The variable encoding of searching individuals grows with the increase of the volume of questions in the question bank, which leads to an increase in computation, and the computation time of political thought test grouping grows with it. To address this shortcoming, this paper uses a segmented real number coding scheme [29]. Individual variables are coded in segments according to question types, and the code coding segments of each question type are relatively independent. According to the question type of the question bank, the segmented real number coding is divided into judgement questions, multiple choice questions, short answer questions, and text entry questions coding area, and the specific coding structure is shown in Figure 6. As can be seen from **Figure 6**, Paper 1 judgement questions are numbered 21, 2, 34, 5, 18, multiple-choice questions are numbered 1, 6, 9, 43, 17, short-answer questions are numbered 1, 6, 9, 43, and text entry questions are numbered 95, 32, 12, 56; Paper 2 judgement questions are numbered 78, 24, 54, 20, 10, multiple-choice questions are numbered 90, 78, 45, 3, 77, and short-answer questions are were numbered 9, 67, 21, 15 and text entry questions were numbered 17, 6, 18, 4. The segmented real number coding scheme mainly consisted of $q_{t1}, q_{t2}, q_{t3}, q_{t4}, q_{t5}$ for judgement questions, $q_{s1}, q_{s2}, q_{s3}, q_{s4}, q_{s5}$ for multiple choice questions, $q_{j1}, q_{j2}, q_{j3}, q_{j4}$ for short answer questions and $q_{w1}, q_{w2}, q_{w3}, q_{w4}$ for text entry questions.

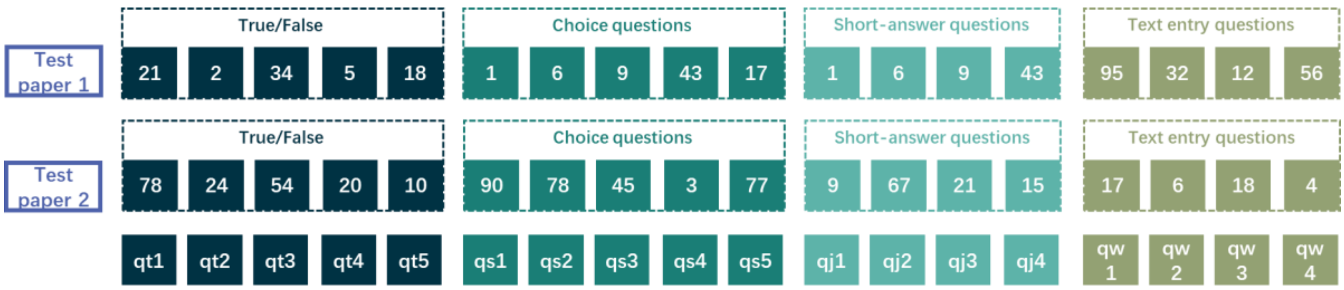


Figure 6 Segmented real number coding scheme

4.2. Individual fitness function design

The individual fitness function is used to generate fitness values for evaluating the individual strengths and weaknesses of test papers by analysing the constraints of each constraint of the grouped papers and combining the properties of the test question indicators. The individual fitness function in this paper is specified as:

$$f\left(q_t, q_s, q_j, q_w\right) = 1 - \frac{\overline{X}}{S} \tag{37}$$

Where, q_t, q_s, q_j, q_w denotes the set of question numbers for the four question types of the paper.

4.3. Intelligent political test paper generation process based on HSSETO algorithm

The essence of the group paper problem is to solve the optimal solution problem with multiple constraints. The process of applying SETO algorithm based on hybrid strategy in the intelligent grouping of university political thought examination is shown in **Figure 7**, and the specific steps are as follows:

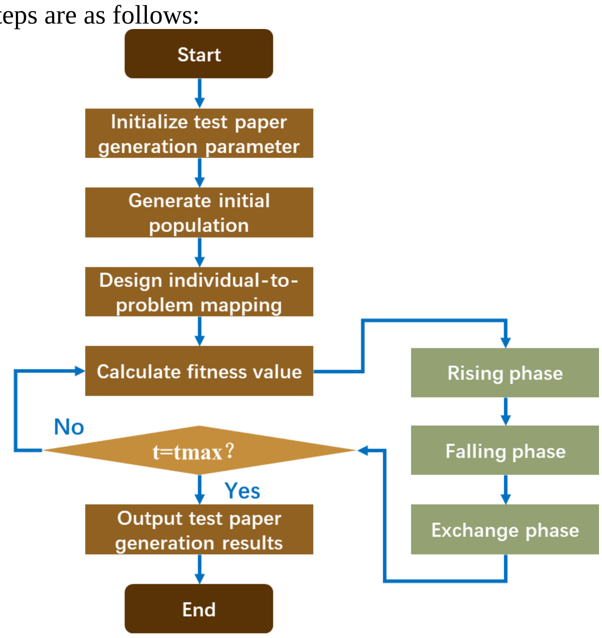


Figure 7 Intelligent political test paper generation method based on improved SETO algorithm

Step 1: Initialise the political thought group paper parameters, including the parameters of the group paper model and the parameters of the improved SETO algorithm. Parameters of political thought test paper grouping model include university political thought question bank, score value, answer time, knowledge points, difficulty, differentiation and related constraints, and parameters of improved SETO algorithm include population size, maximum iteration number, etc.

Step 2: Initialise the search population. Using the given boundary constraints, the search population is selected using the Circle chaotic mapping initialisation strategy.

Step 3: Individual to Group Volume Problem Solution Mapping. The mapping between population individuals to problem solutions is done using a segmented real number encoding approach.

Step 4: Calculate the fitness value of an individual. The fitness value is mainly used to assess the quality index of individual particles relative to the whole group. In this paper, the intelligent grouping model objective function is used as the fitness value function, the larger the fitness value, the better the individual quality, the better the solution.

Step 5: Improve SETO algorithm search to update the population. Optimise the updating of political thought test grouping individuals according to the ascending, descending and trading search phases of the improved SETO algorithm.

Step 6: Determine whether the algorithm termination conditions are met. If the number of search iterations is greater than the maximum number of iterations, terminate the search and output the group volume results; otherwise, continue with **steps 4** to **6**.

5. Experiments and analysis of results

In order to test the effectiveness of the intelligent grouping strategy proposed in this paper for political thought exam, the university political thought test questions are stored in the test bank as an example, and the grouping method proposed in this paper is used to select the university political thought test papers that meet the requirements. MATLAB 2021a is used to write the program, the test environment is Windows 10 system, the processor is AMD Ryzen 9 5900HX with Radeon Graphics, and the memory is 16.0GB.The test parameters include the parameters of grouping and optimisation algorithms, in which the grouping parameters configure the test time as 120 minutes, and the total score of the paper is 100 points; the questions of four types of questions are divided into four groups. The number of questions and scores of the four types of questions are: 10 judgement questions (2 points each), 10 multiple choice questions (3 points each), 5 short answer questions (6 points each), and 2 text entry questions (10 points each). The parameters of each algorithm are shown in **Table 1**.

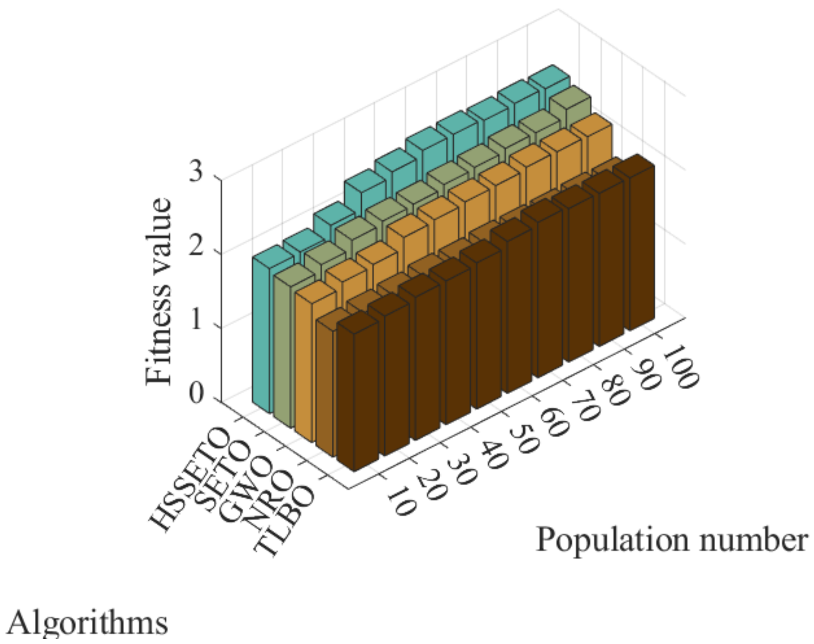
Table 1 Parameter settings for the element construction algorithm

arithmetic	parameterisation
TLBO	Parameter-free optimisation algorithm
NRO	p_{Fi} =0.75, p_{β} =0.1, freq=0.05, Adoption of the Levy distribution strategy
GWO	a=2-2×(iter/itermax)
SETO	Initial number of traders (T)=100
HSSETO	Initial number of traders (T)=100

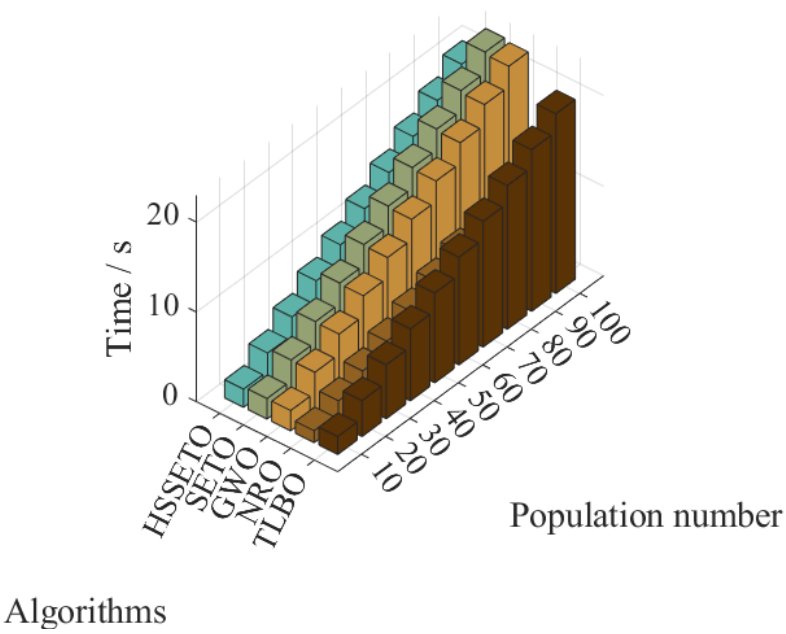
5.1. Algorithm parameter analysis

In order to investigate the impact of HSSETO algorithm parameters on the performance of intelligent grouping strategy for political thought exams, this paper analyses the population size of the HSSETO algorithm.

Figure 8 gives the effect of different population sizes on the performance of the intelligent optimisation-based algorithms for grouping volume strategies. From **Figure 8(a)**, it can be seen that the fitness value of each algorithm tends to increase as the population size increases, and when the population increases to a certain size, the fitness value does not change much, and fluctuates around a certain fitness value; for the HSSETO algorithm, after the number of populations is increased to 50, the value of the grouping volume fitness fluctuates and changes around 2.6, and it does not change much. From **Figure 8(b)**, it can be seen that the group volume elapsed time of each algorithm increases as the population size increases; the slope of the growth of the group volume elapsed time of the SETO algorithm is the largest, and its elapsed time performance is easily affected by the population size. Therefore, in a comprehensive analysis, the population size should take the value of 50 in order to fairly compare the volume formation performance of each algorithm.



(a) Results of the optimal fitness value



(b) Time-consuming results

Figure 8 Impact of population size on the performance of the smart grouping strategy approach

5.2. Analysing the results of the grouping of papers

Based on the above parameter analysis, this subsection compares and analyses the five comparative optimization algorithms from four perspectives: grouping fitness value, average number of iterations, grouping time consumed, and grouping knowledge coverage respectively, and each algorithm is run six times under each working condition, and the specific results are shown in **Figure 9**.

As can be seen from **Figure 9**, in terms of fitness value, the mean and standard deviation of the group volume fitness value based on HSSETO algorithm is better than the other algorithms, and the ranking of the mean value of the group volume fitness value is SETO, GWO, TLBO, and NRO, and the ranking of the standard deviation of the group volume fitness value is NRO, TLBO, SETO, and GWO; in terms of the average number of iterations, the group volume optimisation based on GWO algorithm, NRO algorithm has the lowest mean number of group volume optimisation iterations, and the other algorithms are HSSETO, SETO, TLBO in that order, and the standard deviation of the mean number of group volume optimisation iterations based on the NRO algorithm is the lowest, and the other algorithms are HSSETO, SETO, GWO, TLBO in that order; from the aspect of the group volume time consuming, the group volume based on the NRO algorithm has the lowest mean volume consuming value, and the HSSETO algorithm is better than SETO and TLBO algorithms; from the aspect of knowledge coverage of grouped volumes, the mean value of knowledge coverage of grouped volumes of HSSETO algorithm is better than other algorithms. In summary, the grouped volumes based on HSSETO algorithm obtain better adaptation values and more stable performance in a shorter number of iterations and time.

Algorithms	Fitness value		Average iteration		Time / s		Knowledge coverage	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
TLBO	1.98	6.99e-02	173	15.19	9.18	8.38e-01	0.93	3.93e-02
NRO	1.80	6.34e-02	127	2.28	5.96	6.33e-01	0.89	1.42e-02
GWO	2.21	9.16e-02	127	9.83	9.29	8.95e-01	0.90	1.62e-02
SETO	2.31	7.59e-02	168	6.82	10.01	4.82e-01	0.96	7.56e-03
HSSETO	2.48	6.02e-02	131	4.84	8.02	2.28e-01	0.98	8.05e-03

Figure 9 Comparison of group volume simulation results

6 Conclusion

Intelligent grouping strategy is one of the key technologies for university political thought paper proposition. The current intelligent grouping technology has the defects of slow convergence speed, easy to fall into the local optimal and so on. Aiming at the defects of the current intelligent grouping strategy, this paper proposes an intelligent grouping strategy for political thought examination based on the improved stock market trading optimisation algorithm. By analysing the indicators and conditional constraints of the intelligent grouping problem, designing the objective function, and constructing the intelligent grouping model of political thought; combining the segmented real number coding method and the fitness function, the improved securities market trading optimization algorithm is used to find the optimal solution of the grouping problem. The experimental results show that the intelligent grouping method proposed in this paper can find the optimal solution of intelligent grouping for political thought exam in a shorter time, and the knowledge points of the test questions are covered at a high level, and the difficulty is in line with the demand of the exam paper, and the performance is more stable.

In the subsequent research, machine learning based model for marking university political thought is the next research focus to close the loop on student exams.

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